

Design and validation of a convolutional neural network for fast, model-free blood flow imaging with multiple exposure speckle imaging: supplement

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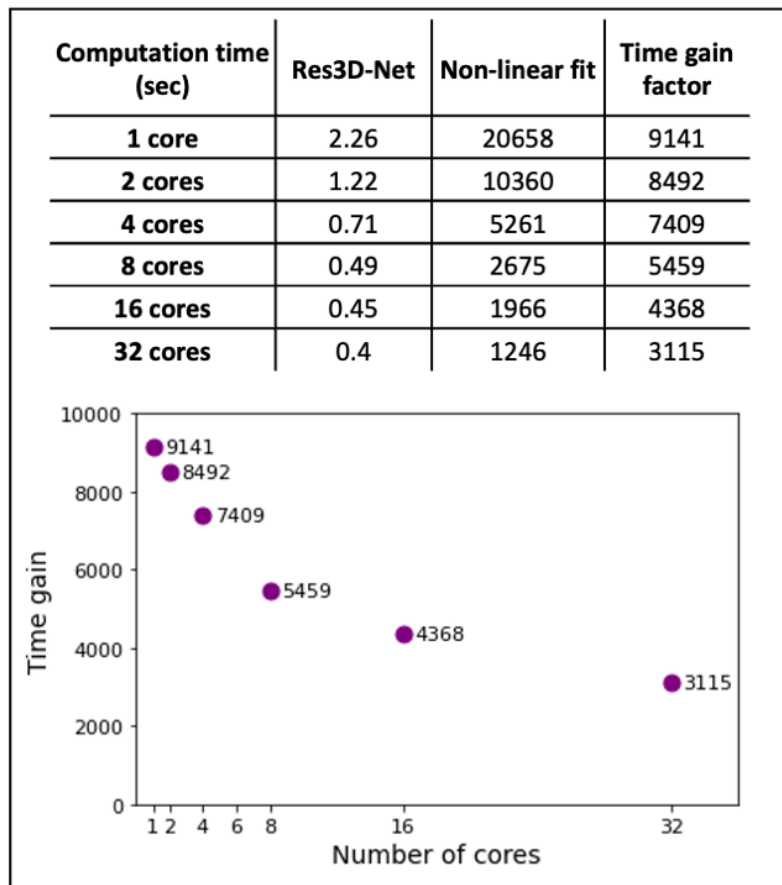
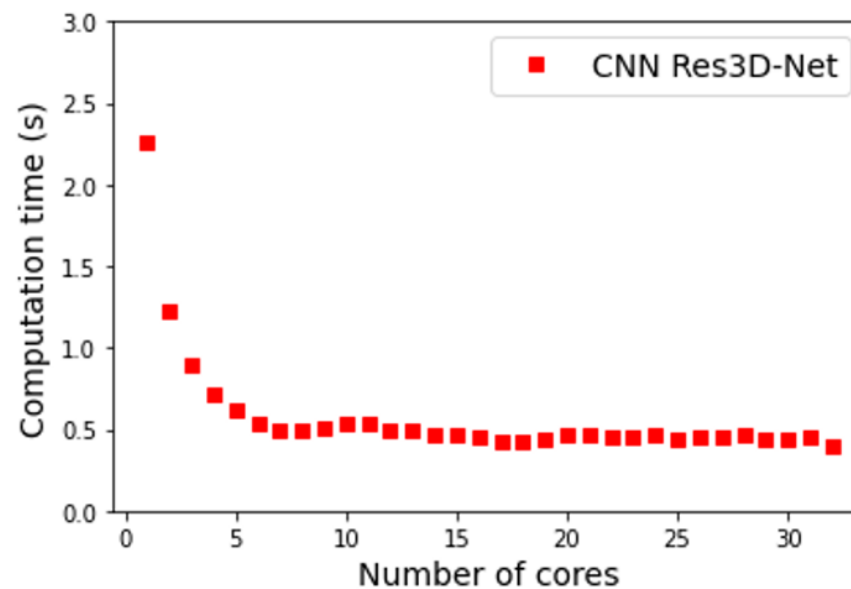
A**B**

Figure S1: Computation time estimated on an image of 700x700 pixels using Python v3.9. (A) Time gain as a function of the number of logical cores used. Time gain is defined as the ratio between the computation time for the non-linear fit and the computation time for CNN. (B) Computation time of the CNN approach as function of the number of used cores.

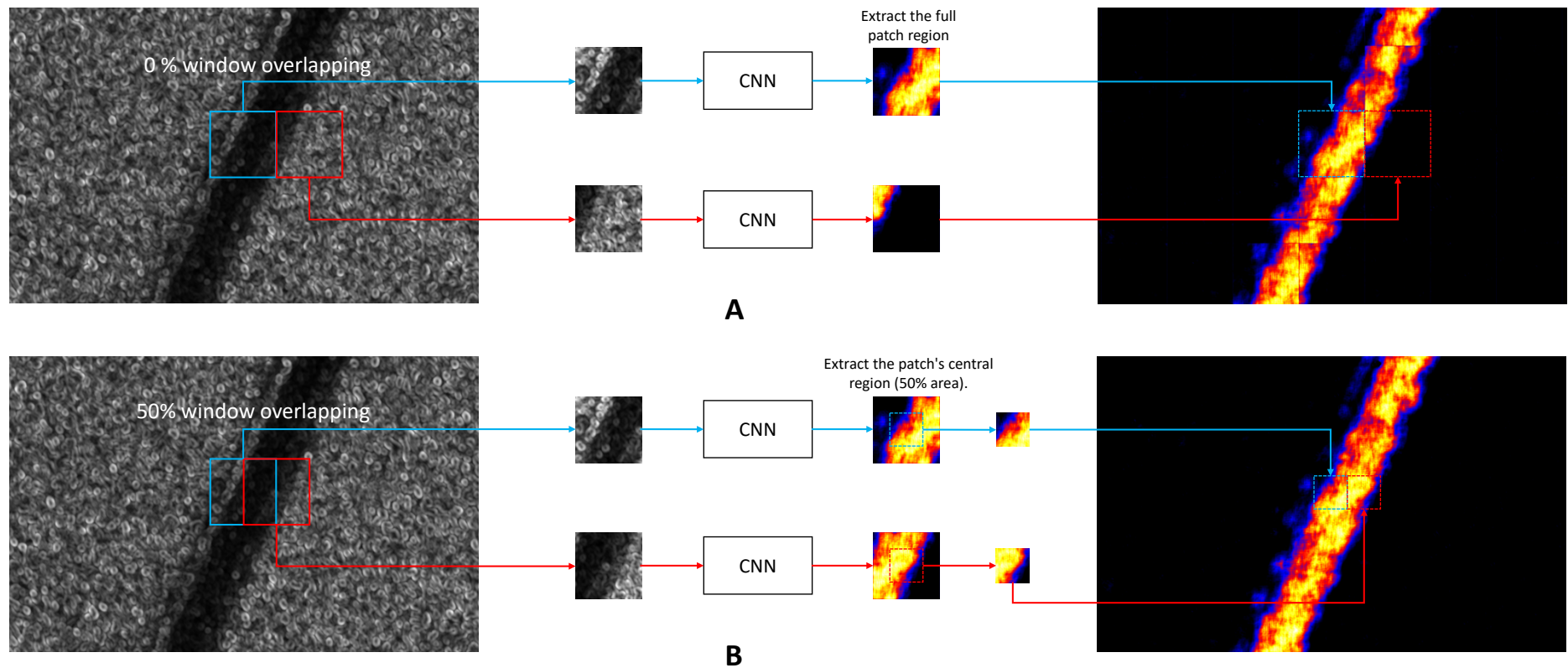


Figure S2: Process of patches extraction, CNN estimation and assembly for prediction of full flow map using (A) non-overlapping patches or (B) half-overlapped patches. A) illustrates the reassembly of the full flow map after the utilization of non-overlapping input patches. Non continuity of the predicted patches due to border effects can potentially leads to inconsistencies during patch assembly and subsequently results in a mosaicking effect across the image. To mitigate mismatches during patch reassembly, we used a sliding window with 50% overlapping to extract the patches from the entire speckle contrast images as shown in B). After the prediction using CNN, the central region (encompassing 50% of the entire area) of the predicted flow patches are used for image reassembly. It is noteworthy that the chosen value of 50% for overlapping is suboptimal, and further optimization efforts should be undertaken to reduce the degree of overlapping for enhancing computational efficiency while avoiding the impact of border effects originating from CNN.

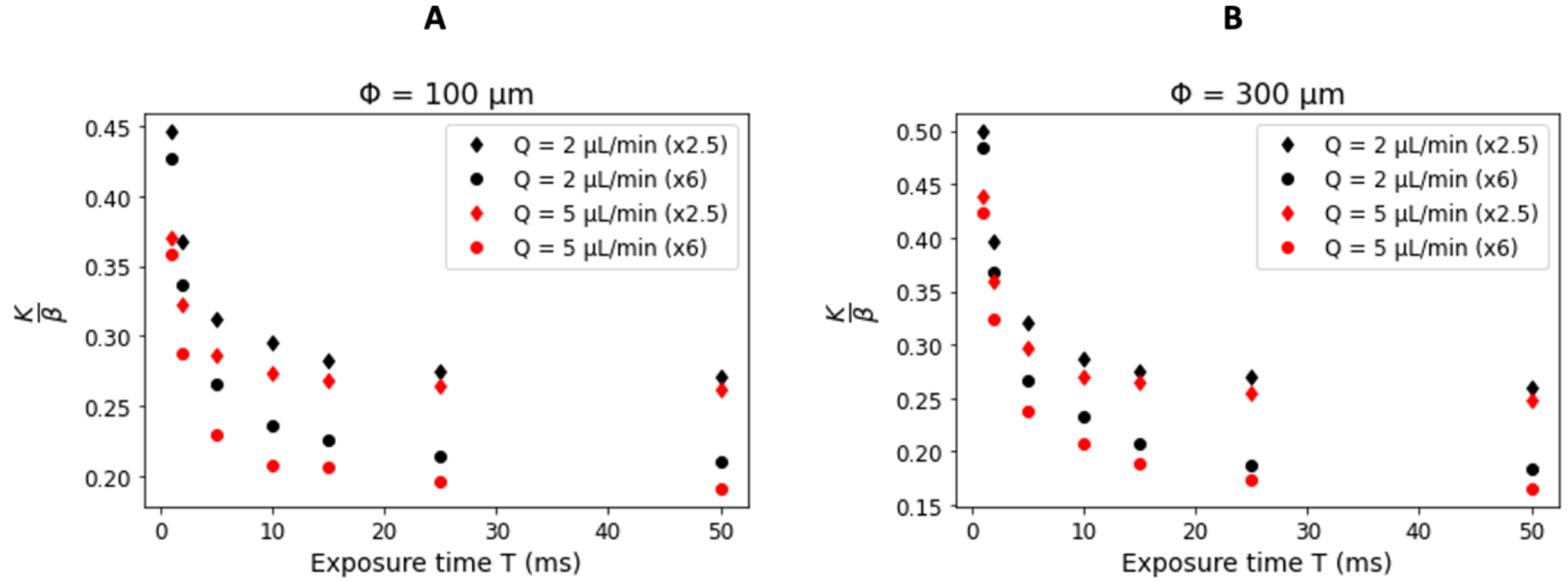


Figure S3. Speckle contrasts as a function of exposure time after normalization to account for spatial averaging at both magnifications. Although the normalization decreases the relative differences between the speckle contrasts calculated at different magnifications for the same flows it did not completely recover the same $K=f(T)$ curves. This indicates that other instrumental parameters participate to the divergence in contrast curves for the same flow. A) For a channel of diameter $\Phi = 100 \mu\text{m}$. B) For a channel diameter $\Phi = 300 \mu\text{m}$. Black symbols correspond to a flow rate of $2 \mu\text{l/min}$, red symbols correspond to a flow rate of $5 \mu\text{l/min}$. Diamonds correspond to x2.5 magnification. Dots correspond to x6 magnification.

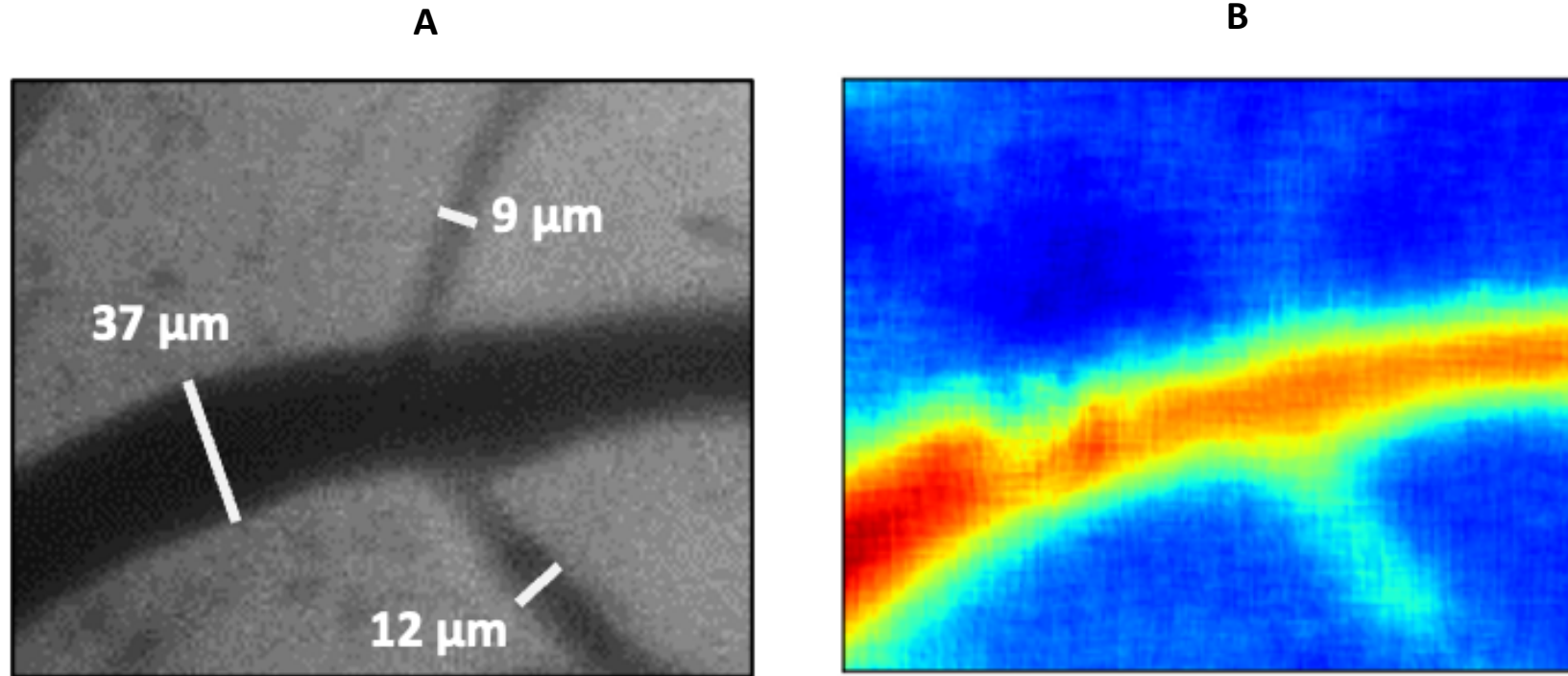


Figure. S4. *In vivo* image obtained on the exposed brain of a different mouse than in Figure 8 to support further the ability of the setup combining synthetic acquisition and Res3D-Net analysis to infer blood relative flow maps within vessels with diameter above 30 μm . Smaller vessels are visible yet not fully resolved. Further work should be carried out to evaluate the ability of the network to interpolate for channels/flows beyond the data used for its training phase, where the smallest channel used had a 40 μm width.